Year: 2017

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DOI: https://doi.org/10.1080/17470218.2016.1192209

Originally published at:
Puskaric, Marin; von Helversen, Bettina; Rieskamp, Jörg (2017). How social and non-social information influence classification decisions: A computational modelling approach. The Quarterly Journal of Experimental Psychology, 70(8):1516-1534.
DOI: https://doi.org/10.1080/17470218.2016.1192209

How social and non-social information influence classification decisions: A computational modeling approach

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Author Note

We would like to thank Laura Wiles for her help with editing the manuscript. This work was supported by SNF research Grant 100014_146169 to the second and third author.

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This is an Accepted Manuscript of an article published by Taylor & Francis Group in The Quarterly Journal of Epxerimental Psychology. This paper is not the copy of record and may not exactly replicate the final, authoritative version of the article.

The final article is available at:

https://www.tandfonline.com/doi/full/10.1080/17470218.2016.1192209

Reference:

Puskaric, M., von Helversen, B., & Rieskamp, J. (2016) How social and non-social information influence classification decisions: A computational modelling approach, *The Quarterly Journal of Experimental Psychology*, 70 (8), 1516-1534, DOI: 10.1080/17470218.2016.1192209

Abstract

Social information such as observing others can improve performance in decision making. In particular, social information has been shown to be useful when finding the best solution on one's own is difficult, costly or dangerous. However, past research suggests that when making decisions people not always consider other people's behavior when it is at odds with their own experiences. Furthermore, the cognitive processes guiding the integration of social information with individual experiences are still under debate. Here, we conducted two experiments to test whether information about other persons' behavior influenced people's decisions in a classification task. Furthermore, we examined how social information is integrated with individual learning experiences by testing different computational models. Our results show that social information had a small but reliable influence on people's classifications. The best computational model suggests that in categorization people first make up their own mind based on the non-social information, which is then updated by the social information.

Word count: 156

Key words: classification; social learning; computational modeling; decision making

Introduction

Opportunities to learn from the behavior and experience of other people are pervasive in everyday life: Children learn to differentiate zoo animals by asking their teacher. Medical students learn to classify healthy from pathologic tissue samples by attending to the experience of their advisors (Meltzoff, Kuhl, Movellan, & Sejnowski, 2009). Indeed, asking or observing others can be an adaptive learning mechanism, because it reduces the necessity for costly trial-and-error learning by allowing the individual to infer the relationship between a particular behavior and its outcome (Campbell-Meiklejohn, Bach, Roepstorff, Dolan, & Frith, 2010; Galef & Yarkovsky, 2009; Henrich & Boyd, 1998; Henrich & McElreath, 2003; McElreath et al., 2005; Meltzoff et al., 2009; Rendell et al., 2011). In this vein, social learning is especially advantageous when it is dangerous, difficult, or costly to explore an environment and gather first-hand experience (Grüter, Leadbeater, & Ratnieks, 2010). Nevertheless, although following social information can be an extremely successful strategy (Rendell et al., 2010), humans do not always follow social information (Franz & Matthews, 2010), but often weight their own experiences or opinions more strongly (Weizsäcker, 2010; Yaniv & Kleinberger, 2000). This raises the question of the degree to which people consider and benefit from social information when performing basic cognitive tasks such as classifications. Furthermore, how social information is integrated into the human decision-making process is still unclear (Biele, Rieskamp, & Gonzalez, 2009; Collins, Percy, Smith, & Kruschke, 2011; Germar, Schlemmer, Krug, Voss, & Mojzisch, 2013; Ruff & Fehr, 2014).

Accordingly, the aim of the current article is twofold: First, we aim to investigate when and how people rely on social information for classifications. Second, we aim to specify how people integrate social information gained from observing others with individual learning experiences by comparing different integration schemata using a computational modeling approach. To investigate these questions we conducted two studies in which participants learnt to make classifications while seeing how others responded in the same task.

Social Information in Classification Decisions

Classification refers to the process of classifying objects into distinct groups or categories based on their characteristics, such as classifying an unknown animal as a cat or a dog using information about its behavior and appearance. Much research in cognitive psychology has been dedicated to understanding how humans learn to make classifications and categorizations (for reviews see, Ashby & Maddox, 2005, 2012; Gelman, 2009). So far, the role of social information in classification has mainly been considered in developmental research, where it has been shown that children benefit from social information, such as observing an adult, because it helps them to discover relevant features and to grasp the rules underlying a specific categorization task (Butler & Markman, 2014; Elsner & Pauen, 2007; Taverna & Peralta, 2012; Wang, Meltzoff, & Williamson, 2015; Wang, Williamson, & Meltzoff, 2015). In comparison to children, relatively little research has investigated the role of social information in adult categorization and classification decisions. As an exception Collins et al. (2011) compared how people use information from social sources (i.e., advice) and non-social sources (i.e., the attributes or features of the object they are classifying) when learning to make classifications. They found that when both types of information were provided simultaneously, people treated social information qualitatively differently from non-social cues; that is, although people learned to ignore redundant non-social information, social information was adhered to even if it carried no additional informative value.

In sum, past research on adults suggests that people pay attention to social information. However, it remains unclear whether adults will also benefit from additional social information when learning to make categorizations or classifications. On the one hand, one might expect that people are able to learn faster and to make better classifications when they receive valid social information. Children seem to benefit from social information (e.g., Butler & Markman, 2014) and Collins et al. (2011) show that people consider social information in situations in which they would ignore similarly valid non-social information, suggesting that people are prone to use social information in their decision process. Furthermore, research in decision making has shown that social information can have a long-lasting influence on behavior in simple decision tasks (Tomlin et al., 2006; Zaki, Schirmer, & Mitchell, 2011) and improves decision accuracy (e.g., Biele et al., 2009; McElreath et al., 2005; Yaniv, 2004).

On the other hand, there are also reasons to believe that social information will not have a great influence on classifications. For one, research on advice taking in decision making suggests that people often put more weight on their own opinion and experiences than on the advice of others, which could lead them to disregard information about other people's behavior (Huber, Klucharev, & Rieskamp, 2015; Yaniv & Kleinberger, 2000). Second, social information can be largely redundant, if the observed person's behavior is based on the same non-social information that individuals have at their disposal and thus does not contain any independent information. Furthermore, some researchers argue that social information is only beneficial if it reflects which pieces of information observed individuals used and how they used them to arrive at a decision, rather than only showing their final decisions (Derex, Godelle, & Raymond, 2012). Last, relying too much on social information may even decrease decision performance, because it could decrease attention to non-social information and thus impair individual learning (Giraldeau, Valone, & Templeton, 2002).

Accordingly, our first goal is to test whether people use information about other people's behavior when making classifications and whether social information facilitates learning.

Integration of social and non-social information

Our second goal is to test different ways that people integrate social information with other sources of information, an issue that has received considerable attention in the decision-making literature (Biele et al., 2009; Biele, Rieskamp, Krugel, & Heekeren, 2011; Collins et al., 2011; Germar et al., 2013; Meshi, Biele, Korn, & Heekeren, 2012; Ruff & Fehr, 2014; Yaniv, 2004; Yaniv & Kleinberger, 2000; Zaki et al., 2011). Here, we test two general hypotheses regarding the integration process. The first hypothesis is that social information and non-social information are evaluated in a single evaluation process (Germar et al., 2013; Ruff & Fehr, 2014). Accordingly, when, for instance, classifying a mushroom as edible or toxic based on the mushroom's attributes and other people's advice, this means that the social information is used in the same way as non-social information such as the mushroom's cap color or smell. Furthermore, it implies that social information can bias how people process the non-social information in their decision. In this vein, Germar et al. (2013) found that in simple perceptual decisions, providing information about other people's behavior not only biased the decision in the direction of the other person, but altered the cognitive process underlying the decision.

Alternatively, according to the second hypothesis, processing of individual and social information could happen in a computationally segregated way following a two-step integration process (e.g., Behrens, Hunt, & Rushworth, 2009; Collins et al., 2011); that is, people might in the first step form an individual judgment regarding the mushroom's edibility based on the mushroom's attributes. Then, in a second step the quality of the received social information is evaluated independently and used to update the individual judgment. Accordingly, when classifying the mushroom, people first form their own opinion based on the mushroom's attributes but then adjust this opinion based on the social information. This hypothesis implies that people's processing of the non-social information should not be affected by the social information. This, in turn, could make it easier for people to make a categorization for cases in which social information is revoked or not available. The idea of a two-step process is supported by the findings of Collins et al. (2011) that social information is treated qualitatively differently from non-social information. Furthermore, neuroscience studies have reported that non-social and social information are processed in distinct areas of the brain that are integrated for a final decision (Behrens, Hunt, Woolrich, & Rushworth, 2008; Burke, Tobler, Baddeley, & Schultz, 2010).

In the current article, we test the two competing hypotheses of whether a single-step or a two-step integration process best described how people use social information in classification by following a computational modeling approach. In the following, we describe the different categorization models and then report two studies testing them.

Modeling the use of social information in classification

To model participants' classification decisions we relied on an exemplar model framework (Collins et al., 2011; Kruschke, 1992; Medin & Schaffer, 1978; Nosofsky & Johansen, 2000; Nosofsky, 1986). Exemplar models assume that people make classifications based on the similarity of the object under evaluation to previously encountered exemplars. For instance, when determining whether a mushroom is edible, the exemplar model assumes that people recall the edibility of previously encountered mushrooms and use this to determine whether the newly encountered one can also be eaten. The probability with which the mushroom is classified is a function of its similarity to the retrieved edible mushrooms in comparison to the retrieved non-edible mushrooms. Exemplar models are frequently used to understand the cognitive processes underlying classifications and have been successfully employed to explain a large range of behavioral phenomena (Hoffmann, von Helversen, & Rieskamp, 2014; Nosofsky & Johansen, 2000; Olsson, Juslin, & Olsson, 2006; Scheibehenne, von Helversen, & Rieskamp, 2015; von Helversen, Karlsson, Mata, & Wilke, 2013). Here, we used the General Context Model (GCM; Nosofsky, 1986; Nosofsky & Johansen, 2000) to describe classifications using non-social information and then extended the GCM to incorporate social information according to either a single-step or a two-step integration process.

Generalized Context Model (GCM). The GCM assumes that an object is classified by comparing the presented object to the exemplars that are stored in memory for each category and calculating the similarity between the object and the respective exemplars. The object is then classified into the category with the higher overall similarity score.

The similarity between an object and an exemplar is assumed to be a decreasing function of the distance between the two objects in a multidimensional space that is determined by the objects' attributes (also called cue dimensions) and can be altered by attention processes. Mathematically, the distance *d* between an object *i* and an exemplar *j* is described by:

$$d_{ij} = \left[\sum_m w_m \cdot \left| x_{im} - x_{jm} \right|^r \right]^{1/r} \qquad (1)$$

where w_m are the attention weights that govern the amount of attention that an observer gives to each attribute or cue dimension *m*. The attention weights are constrained to add to one. The parameter *r* defines the distance metric of the space and *x* denotes the value that an object or exemplar has on the respective cue dimension.

The distance is then used to define the similarity of object *i* to exemplar *j*, as described by:

$$s_{ij} = \exp(-c \cdot d_{ij}), \qquad (2)$$

where *c* is the sensitivity parameter, which defines the rate at which similarity declines with distance. Low values of sensitivity mean that exemplars that are separated by large distances in psychological space will still be judged as similar, whereas high values of sensitivity mean that close exemplars will still be judged as dissimilar.

Similarity between the objects and the exemplars is then used to compute the probability that an object *i* is classified into a category *J:*

$$P(J \mid i) = \frac{\left(\sum_{j \in J} s_{ij}\right)^{\gamma}}{\left[\sum_{K}\left(\sum_{k \in K} s_{ik}\right)^{\gamma}\right]}, \qquad (3)$$

where K are all possible categories and j denotes the exemplars of J. The parameter γ is a response-scaling parameter (Ashby & Maddox, 1993; Nosofsky & Johansen, 2000).

Constant Probability Model (CPM). In addition to the GCM we included a baseline model that ignores the specific cue patterns and just assumes that each category is chosen with a constant probability. We implemented this model with a single free parameter that is estimated and denotes the constant probability with which one category is chosen. This baseline model acts as a performance threshold for the other models by representing very simplistic behavior. The social models need to outperform the CPM to show their psychological plausibility.

Social classification models

To test how people integrate social information with the non-social information when making classifications, we implemented two extended versions of the GCM that correspond to the idea of a single-step or a two-step integration process.

Single-step integration: The Social CUE Model (CUE)

A single-step integration process assumes that people integrate social information when forming their own opinion and thus essentially treat social information in the same way as non-social information. In this vein, the CUE model is computationally similar to the GCM. Assuming that social information is treated just like a further (non-social) attribute/cue would be treated, it simply extends it by an additional cue dimension (the social information). This implies that the social information is an integral part of the evaluation process and that social information can alter the evaluation process by influencing how the other (non-social) cues are processed. Due to the interaction between the cues (i.e., non-social and social) this integration mechanism also implies that the non-social cue can have an impact on how the social cue affects the categorization. Accordingly, the effect of social information can be moderated by the presence and absence of the other cues presented.

Two-step integration

A two-step integration process assumes that people first form their independent judgment based on the non-social information and then integrate this judgment with the social information; that is, non-social and social information lead to two independent classifications specifying the probability with which a category will be chosen. These two judgments are then integrated in a second step to lead to the final classification probability. We implemented two versions of two-step integration models: (1) the Social Choice Model GCM and (2) the Social Choice Model CPM.

Social Choice Model GCM (SC_{GCM}). The SC_{GCM} assumes that individuals rely on an exemplar-based process as described by the GCM when determining the probability with which they would classify an object into the respective categories based on the non-social cues (i.e., the objects' attributes). In a second step, they then integrate the classification probability derived from the non-social cues with the social information by weighting and adding the two probabilities. If no social information is available the model defaults to the GCM:

$$P(J \mid i) = (1 - \omega) \cdot P_{GCM} + \omega \cdot P_{SI}, \quad (4)$$

where the weight given to the social information is a free parameter ω that varies between 0 and 1. P_{GCM} is the result of the GCM classification process and P_{SI} is the social information in the current trial, where 1 corresponds to category rain and 0 corresponds to category sun. High values of ω mean that the participant is strongly following the social information, whereas low values of ω indicate that the participant is predominantly using individually acquired knowledge for the classification decision. When no social information is present, ω is automatically set to 0.

Social Choice Model CPM (SC_{CPM}). The SC_{CPM} assumes that social information is integrated with the other information in the same way as the SC_{GCM}, see Equation 4. However, instead of determining the classification probability based on non-social information according to an exemplar-based process, it assumes that people ignore the information on the non-social cues and only develop a constant probability for judging the objects as belonging to one of the two categories. This individual classification probability is then weighted and integrated with the social information.

Study 1

The goal of Study 1 was to investigate whether people learn to rely on valid social information when making classifications and to test the different information integration schemata against each other. For this, we conducted an experiment in which participants had to learn to classify objects described by five binary cues into two categories. In an individual condition participants performed the task without receiving social information. In addition, we added two social conditions: In the single-social condition participants faced the identical classification task, but additionally received information in the training phase about the trial-by-trial decisions of a single well-performing, real participant from the individual condition. In the test phase, social information was constructed by the experimenter to test the hypotheses in a more controlled manner. In addition, we included a second social condition in which participants performed the identical social learning task, but were informed that the social information came from the aggregated decision of a group of 20 participants. We included the "multi-social" condition to increase the effect of the social information on classifications. Group size is a strong moderator of social influence, with larger groups exerting stronger influence than single individuals (Bond, 2005; Bond & Smith, 1996;

Morgan, Rendell, Ehn, Hoppitt, & Laland, 2012). In particular, larger groups have been shown to increase conformity and are recognized as being more accurate (Latané, 1981; Mannes, 2009).

Method

Participants

Sixty participants (40 female, 20 male; M_{age} = 23.5, range 21–42 years) were recruited from the student participant pool of the University of Basel, with 20 participants taking part in each condition. The duration of the experiment was approximately 45 minutes. Participants received an hourly compensation and a performance-dependent bonus. On average they gained 24.8 Swiss francs in the individual condition, 25.2 Swiss francs in the single-social condition, and 25.1 Swiss francs in the multi-social condition. Sample size was based on those employed in similar tasks (e.g., Mata, von Helversen, Karlsson, & Cüpper, 2012).

Classification Task

Participants had to solve a categorization task, which bears similarity to the *weather prediction task* (Gluck, Shohamy, & Myers, 2002; Knowlton, Squire, & Gluck, 1994). Participants saw objects that consisted of five binary cues and their task was to decide whether the object predicted rain or sun. Each cue consisted of a geometric pattern that could appear in either the color blue or red. All cues were similarly predictive but differed as to whether red or blue indicated that rain was more probable. Cue validities, defined as the proportion of cases in which a given cue predicted the correct classification, were .55, .55, .55, .65 and .65 for cues 1 to 6 respectively. For cues 1, 4, and 5 the color blue was predictive of rain and for cues 2 and 3 the color red was predictive of rain. Of the 32 possible objects, we used 30 (excluding the objects with only red or only blue patterns) in the study. Each object belonged to either the rain or the sun category (see Table 1). The experiment consisted of a training and a test phase. In the individual condition, the training phase was composed of 200 trials, consisting of 20 training objects that were repeated in 10 blocks. The order of the objects was randomized within each block. In each trial, participants were presented with one object and had to decide whether it predicted rain or sun (see Figure 1A). After classifying the object, participants were provided with feedback on whether their decision was correct or not and then continued with the next trial. After participants completed the training phase, they continued with the test phase. In the individual learning condition, the test phase consisted of 160 trials, consisting of 20 objects that were repeated in 8 blocks. The 20 objects consisted of 10 new objects and 10 known objects from the training phase. In the test phase, participants did not receive any feedback on their classification decisions.

In the two social conditions, the training phase was identical to the training phase in the individual condition, with the exception that in every second trial participants additionally saw the decision that a preselected participant from the individual condition had made (see Figure 1B and C). We did not provide social information in every trial because we wanted to encourage participants to learn about the non-social information and to be able to compare classifications with and without social information. The two social conditions differed only in the framing of social information; in the single-social condition participants were informed that they would observe a single decision maker. In the multi-social condition they were informed that they would observe the majority decision of 20 decision makers. As social information we chose the responses of a participant from the individual condition who had mastered the task very well and had a steady learning curve (see also Figure 2, panel A): The classification accuracy of the observed participant started at chance in the first block (45%) and settled at a high number of correct answers in the last block (95%). Each object in the training phase was shown with and without social information in equal proportions.

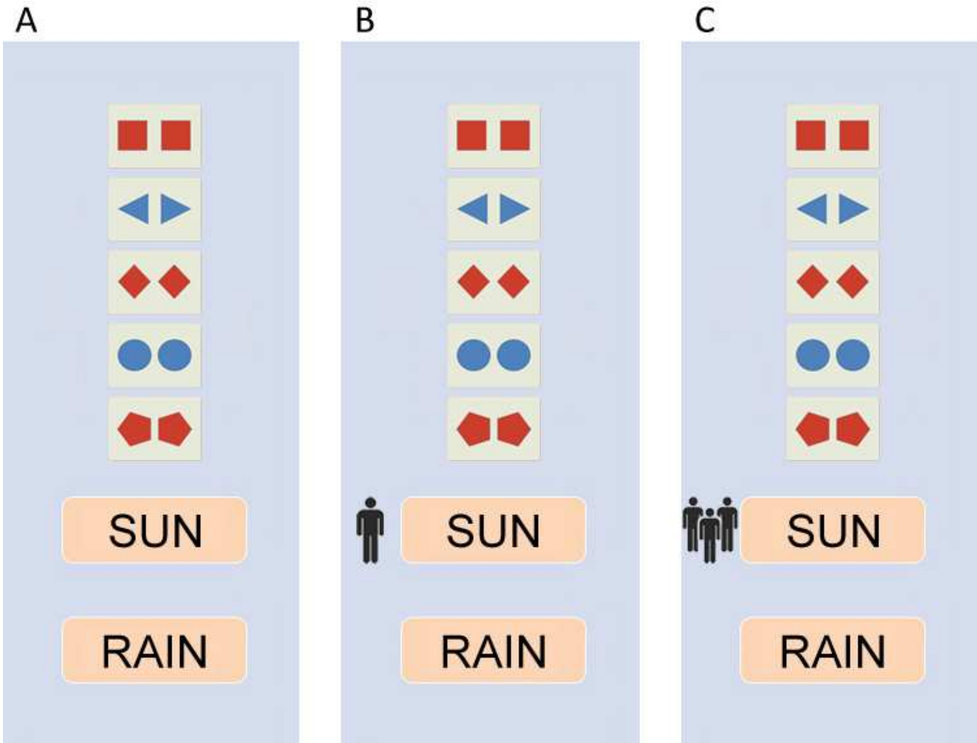

Figure 1. The figure illustrates how the different objects were presented to the participants in Study 1. The left panel (A) shows an example trial of the individual condition or a non-social trial in one of the social conditions. The middle panel (B) shows a social trial of the single-social condition, while the right panel (C) shows a social trial of the multi-social condition. Stick figures indicated the social information (i.e., the decision of the presented participant/s) in a given trial.

The test phase in the social conditions contained 240 trials, consisting of 60 objects, that were repeated 4 times. These 60 objects consisted of the 10 new objects from the test phase in the individual condition shown four times: once with social information indicating rain, once with social information indicating sun, and twice without social information to keep the ratio of trials with and without social information equal (40 objects, see Table 1). In addition, 10 old objects from the training phase were shown once without social information and once with the social information reflecting the actual choices of the preselected participant to ensure that the observed individual choices were still believable (20 objects).

Objects 6, 9, 23, and 26 in Table 1 were presented with social information indicating rain and objects 2, 4, 10, 16 and 20 with social information indicating sun. The order of the objects within a block was randomized but the same for all participants.

Procedure

The procedure was identical in all three conditions: Participants first received a consent form printed on paper, in which they agreed to participate in the study. Then they started the computer-based classification task. After finishing the task, participants received either 20 Swiss francs or participation credit for attendance. Additionally, participants could gain a bonus of up to 5 Swiss francs, depending on their performance in the test phase of the experiment: For each correct answer they received 0.02 Swiss francs, for each incorrect answer 0.02 Swiss francs were deducted from the bonus. The task was performed on a computer using Windows 7 operating system on a PC with 22-inch screen and a resolution of 1680 x 1050 pixels and the software “Inquisit” (Millisecond Software, Seattle, USA). The instructions and stimuli used in the study can be retrieved from: 10.6084/m9.figshare.2065818

We confirm that for all experiments in this article we reported all measures, conditions, and data.

Results

Performance

Training. We analyzed whether participants in each condition had learned to correctly classify the objects and whether social information had an effect on performance. Performance was measured as the percentage of correct classifications within a block. On average participants were able to improve their performance in all three conditions (see Figure 2, panel A). A repeated measures analysis of variance (ANOVA), with block as a within-participant factor and condition as between-participant factor, indicated a significant main effect of block, $F(6.55, 373.32) = 28$, $p < .001$, $\eta^2 = .33$, but no significant main effect of condition, $F(2, 57) = 2.03$, $p = .141$, $\eta^2 = .07$, and no significant interaction between block and condition, $F(13.10, 373.32) = .79$, $p = .667$, $\eta^2 = .03$. The degrees of freedom were corrected according to the Greenhouse–Geisser method, because the assumption of sphericity was violated, $\chi^2(44) = 81.97$, $p < .001$. In all following analyses of variance we relied on the Greenhouse–Geisser correction method, if the assumption of sphericity was violated.

These results suggest that overall participants learnt to solve the classification task, but that including social information did not affect learning speed or overall performance.

Test.

In the test phase participants overall performed better with the old objects than the new objects in the individual condition ($M_{old} = 71.9$, $SD = 49.9$ vs. $M_{new} = 53.4$, $SD = 45$) as well as in the social conditions (single social: $M_{old} = 68.3$, $SD = 46.6$ vs. $M_{new} = 50.8$, $SD = 50$; multi-social: $M_{old} = 77.8$, $SD = 41.6$ vs. $M_{new} = 49$, $SD = 50$). To investigate how social information affected classification performance we compared (a) how participants in the social conditions performed compared to the individual condition and (b) how within the social conditions providing no, correct, and incorrect social information influenced performance. For this analysis we focused on the new test objects, because they were all presented with no, correct, and incorrect social information and thus provide the most appropriate test.[1] The pattern of results, however, is the same when considering all objects in

[1] In the individual condition the test objects did not include any social information and were each presented 8 times, whereas in the social conditions each new test object was presented 8 times with no, 4 times with incorrect, and 4 times with correct social information. For the ANOVA we calculated performance for the objects with no social information based on the 8 repetitions in the individual and social conditions. To calculate performance for the objects with correct and incorrect social information we used the 4 presentations with the respective social information in the social conditions. In the individual condition we calculated performance by randomly drawing for each test object 4 repetitions from the 8 repetitions (once for the correct and once for the incorrect comparison) to keep the number of repetitions comparable to the social conditions.

the test phase. As illustrated in Figure 2 (panel B) a repeated measurement ANOVA with condition (individual, single-social, multi-social) as a between-subjects factor and quality of social information (coded: incorrect = -1, none = 0, correct = 1) as a within-subject factor showed no significant main effect of condition, $F(2,57) = 1.29$, $p = .28$, $\eta^2 = .04$. However, we found a significant main effect of quality of information, $F(1.09, 62.0) = 22.5$, $p = .001$, $\eta^2 = .28$, suggesting that performance increased from incorrect to none to correct social information, linear trend: $F(2,57) = 9.33$, $p < .001$, $\eta^2 = .25$. Furthermore, a significant interaction between quality of information and condition, $F(2.17, 62.0) = 8.98$, $p < .001$, $\eta^2 = .24$, indicated that the effect of condition differed depending on the quality of information. Follow-up contrasts comparing the individual condition to the two social conditions for the three types of social information separately suggested that when incorrect information was presented, participants in the social conditions performed worse than participants in the individual condition, $t(57) = -4.22$, $p < .001$. Conversely, when correct social information was presented participants in the social conditions performed better than participants in the individual condition, $t(57) = 2.7$, $p = .009$. There was no significant difference in performance when no social information was shown, $t(57) = -1.80$, $p = .077$.

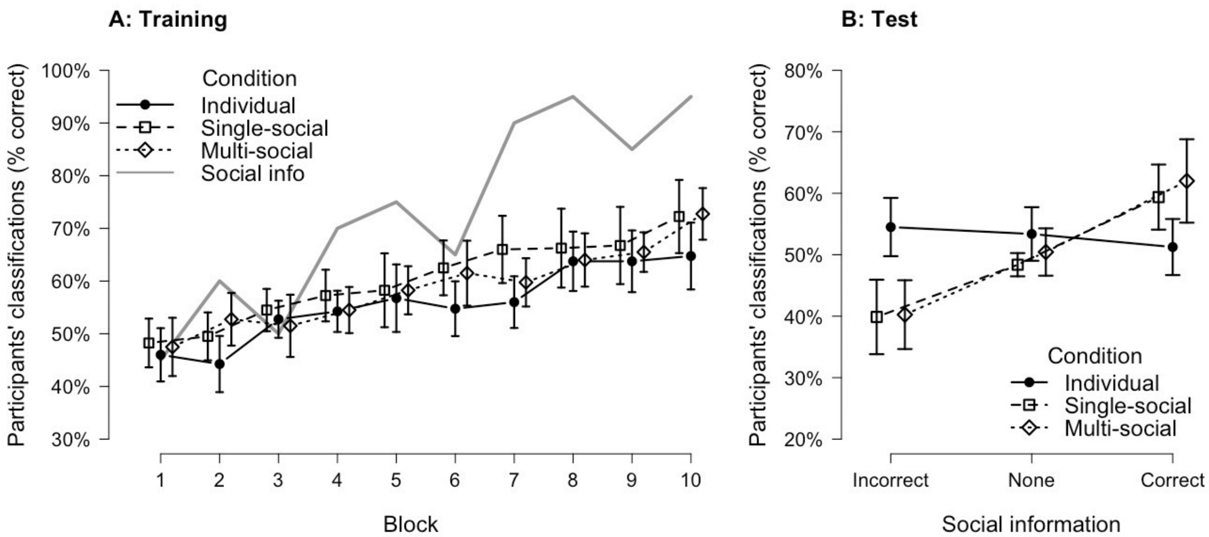

Figure 2. The left panel (A: Training) shows the learning performance in the training phase of Study 1. Each block consists of 20 trials. Superimposed is the performance of the

participant whose data was used as social information. Error bars denote a 95% confidence interval. The right panel (B: Test) shows the performance as a function of the information quality and the social condition in the test phase of Study 1. Please note that in the individual condition no social information was presented. The labels "incorrect", "none" and "correct" social information denote the respective objects that were presented with incorrect, no or correct social information in the social conditions (see also Footnote 1). Error bars indicate a 95% confidence interval. Please note the different scaling of the y-axis across panels.

In sum, the study provided evidence that on average participants considered the social information and integrated it in their decision process, although social information on average did not improve performance. In the next step we used computational modeling to test which model can best describe how social information is integrated for the classification.

Model comparison

To test the models against each other we performed estimations using the individual data of each participant. Specifically, we estimated each model with the participants' responses in the last 60 trials of the training phase and all trials of the test phase (i.e., in total 220 trials in the individual condition and 300 trials in the social conditions), minimizing the negative log likelihood (LL). When estimating the parameters of the GCM, we assumed that participants could retrieve the training objects (see Table 1) as their knowledge base. To find the parameters that minimized LL we first performed a grid search (Lewandowsky & Farrell, 2010). The grid search explores a number of possible combinations of parameter values and makes a rough estimation of the best-fitting set of parameter values. This set was then used as starting values for a more detailed parameter estimation using "fmincon", a constrained nonlinear optimization algorithm implemented in Matlab, to find the set of parameters that minimize LL (Coleman & Li, 1996; Lagarias, Reeds, Wright, & Wright, 1998).

The estimation procedure for the CUE model was identical, with the only difference being that social information was included as an additional cue, which was coded -1 for category "sun", 1 for category "rain", and 0 if no social information was observed.

To estimate the SC_{GCM}, we used the choice probabilities generated by the GCM for the respective participants and the observed social information (coded 0 for sun and 1 for rain) as inputs. Analogous, we used the probabilities generated by the constant-choice model and social information as inputs for the SC_{CPM} model. The constant-choice model was estimated by defining a single parameter that captured the participant's propensity to classify objects into the category rain. The social weight parameter as denoted in Equation 4 was first estimated using a grid-search and subsequently the estimation was optimized using the fmincon algorithm. Table 2 summarizes the model evaluation results. To compare competing models against each other, we used the Bayesian information criterion (BIC; Lewandowsky & Farrell, 2010; Schwarz, 1978). The BIC is a measure of model performance that accounts for model complexity by incorporating a punishment term for the number of free parameters:

$$\mathrm{BIC} = -2 \times \mathrm{LL} + \mathrm{d} \times \log(N), \tag{5}$$

where N is the number of data points, d is the number of free parameters of the tested model, and LL corresponds to the log-likelihood of the tested model: The GCM had five free parameters, the five attention parameters for the five cues had to add up to a value of 1, implying four free parameters and the sensitivity parameter c. Following past work the distance parameter r and the response-scaling parameter γ were set to a value of 1 (Mata et al., 2012; Nosofsky & Johansen, 2000; Olsson, Wennerholm, & Lyxzen, 2004). The social cue model and the SC_{GCM} each had an additional free parameter coding the reliance on the social information. The SC_{CPM} had one free parameter, the bias, and the SC_{CPM} two free parameters, the bias and the weight given to the social information. To compare the models in a meaningful way, we use Bayesian model weighting (Kass & Raftery, 1995), which is a measure of relative strength of evidence for the models per participant:

$$w_M = \frac{\exp\left(-\frac{1}{2}\Delta BIC_M\right)}{\sum_i \exp\left(-\frac{1}{2}\Delta BIC_i\right)}, \tag{6}$$

where ΔBIC_M is the BIC difference between a specific model M and the best model and ΔBIC_i is the difference between the best model and all models i in our set. The Bayesian model weights provide information about the amount of evidence in favor of a given model for each participant. Evidence is subdivided into weak evidence (.25 to .5), positive evidence (.5 to .87), strong evidence (.87 to .97), and very strong evidence (> .97), see Table 2. Figure 3 gives an overview of how many participants were best described by each model and the evidence for each model. In the individual learning condition, 14 (70%) participants were best described by the GCM and 6 (30%) by the CPM. Taking the two social learning conditions together, half of the participants were best described by a non-social model, 17 (42.5%) by the GCM, and 3 (7.5%) by the CPM. The remaining 20 (50%) participants were best described by a social model, with 7 (17.5%) assigned to the SC_{GCM}, 9 (22.5%) to the SC_{CPM}, and 4 (10%) to the CUE model.

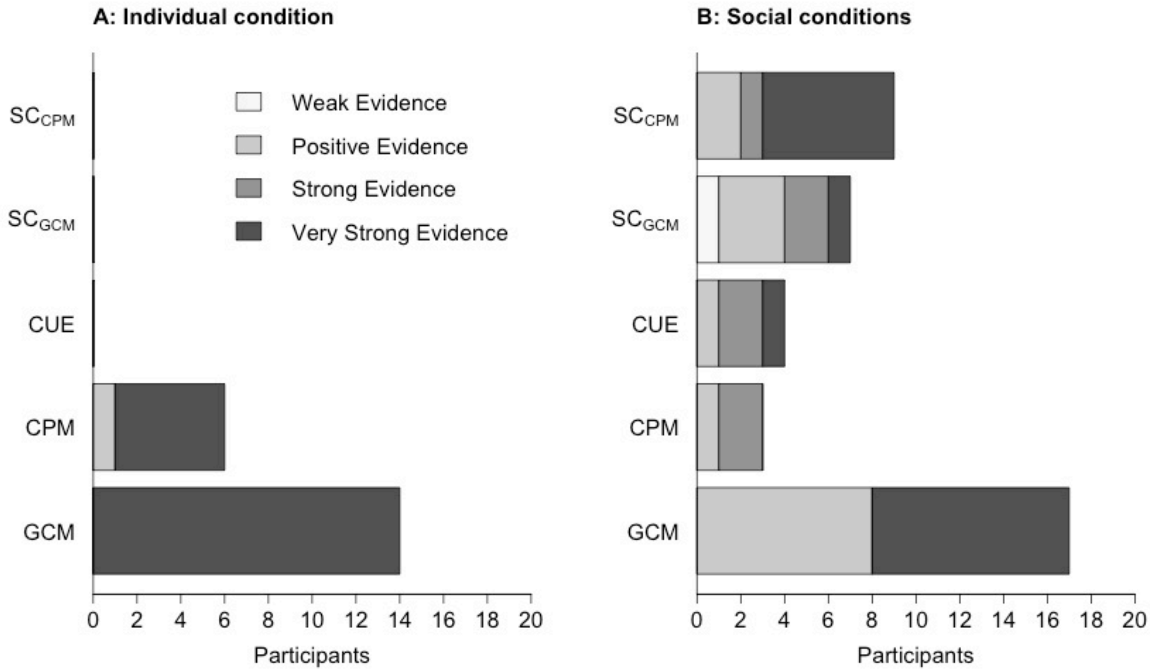

Figure 3. Evidence for each model per participant of Study 1. The left panel (A: Individual condition) shows evidence for the individual condition and the right panel (B: Social conditions) for the two social conditions put together. GCM = general context model; CPM = constant probability model; CUE = cue model; SC_{GCM} = social choice (general context model); SC_{CPM} = social choice (constant probability model).

Comparing the strength of evidence in favor of the different integration mechanisms for social and non-social information suggested that the evidence favored the two-stage integration mechanism of the SC_{GCM} and the SC_{CPM} by a ratio of 2.5 across all participants over the single process of the CUE model (Wagenmakers & Farrell, 2004). We compute the evidence ratio adapting the following equation (Wagenmakers & Farrell, 2004, p. 195):

$$ratio = \frac{w_{SC(GCM)}(BIC) + w_{SC(CPM)}(BIC)}{w_{CUE}(BIC)}, \tag{7}$$

where *w* is the Bayesian weight of the corresponding model.

Finally a comparison between the two social choice models showed that the SC_{CPM} model was 1.2 times more likely than the SC_{GCM} model.

To show that the models are providing a good absolute fit to the data, we visually contrast classification probabilities of the main models of interest and the average classification probabilities of the participants best described by the respective model (Figure 4). The comparison shows that participants who were described by a social model tend to classify objects more decisively when encountered with social information, which can be captured by the social models but not by the GCM. This is also supported by an analysis comparing how often participants' decisions matched the social information. The decisions of the participants classified to the GCM matched the social information less frequently than the decisions of participants classified to one of the social models, $M_{\text{GCM}} = 58.8$; $SD = 5.4$, versus $M_{\text{social}} = 73.6$; $SD = 8.5$, $t(35) = 6.16$, $p < .001$, $d = 2.07$. The data and the matlab code used to fit the models can be retrieved from: 10.6084/m9.figshare.2065818

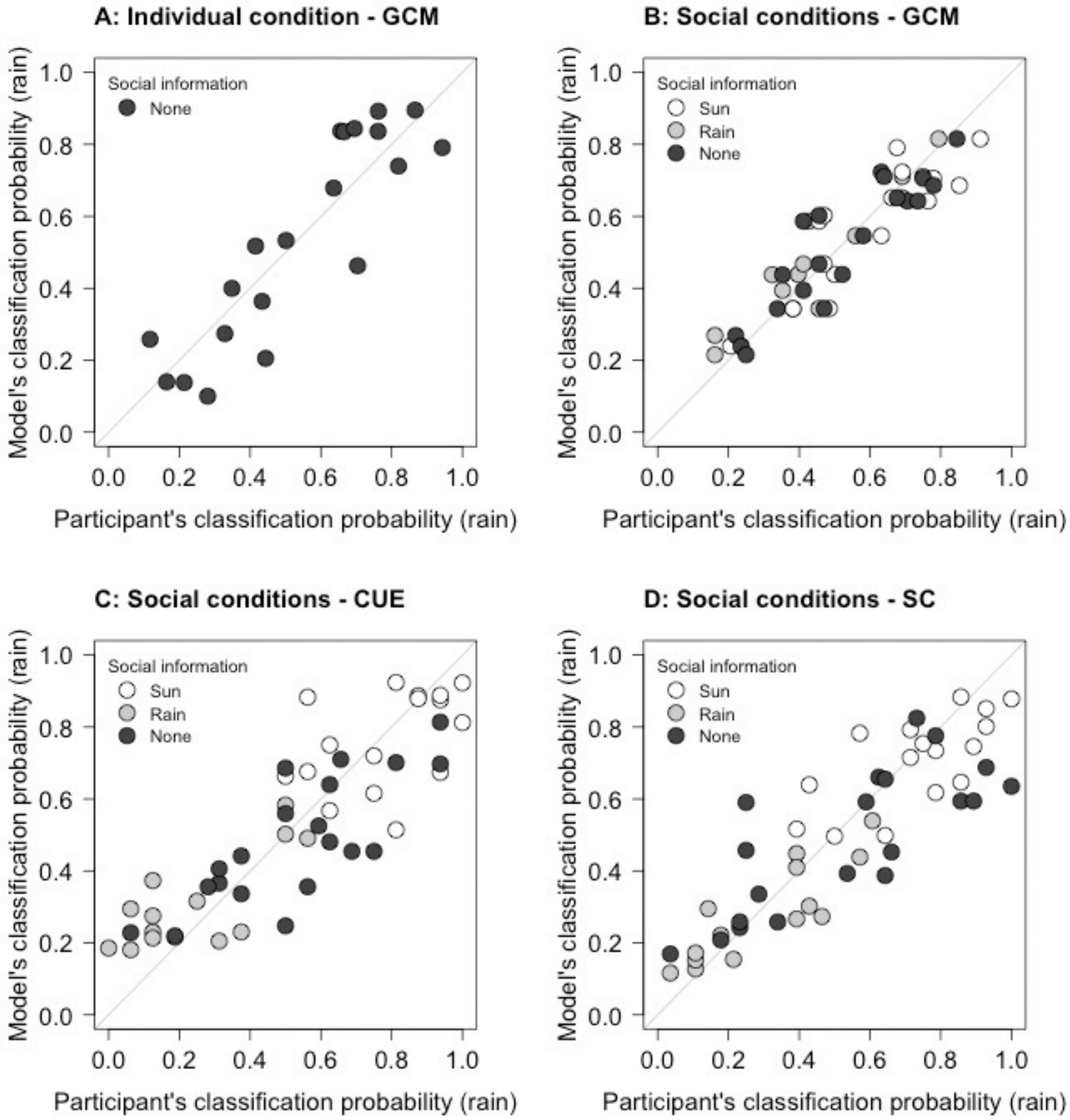

Figure 4. The figure shows scatter plots of participants' classification probabilities and model predictions in the individual and social conditions. Panel A shows participants' and the GCM's classification probabilities for the individual condition. Panels B to D show participants' and model's classification probabilities for subjects of both social conditions jointly, with panel B showing the GCM, panel C the CUE model, and panel D the SC model. Each panel shows the data of the participants who were described best by the respective model.

In sum, our results suggest that about half of the participants relied on social information. In addition, almost all participants who used social information were better described by models using a two-stage integration mechanism.

Discussion of Study 1

The goal of Study 1 was to investigate how social information influences the way people learn to make classifications and to study the integration of social and non-social information. Unlike in value-based learning tasks (e.g., Biele et al., 2009, 2011), we did not find an overall benefit of social information in classification performance, even though following the observed social information would have led to better decisions for the majority of participants. However, a more detailed behavioral analysis and modeling analyses showed that about half of the participants used the social information in their decision process. This resonates with previous work on advice taking showing that people consider social information when making decisions (e.g., Biele et al., 2009, 2011; Collins et al., 2011) but often assign less weight to it than to their own opinion (Weizsäcker, 2010; Yaniv & Kleinberger, 2000). Unexpectedly, we did not find a difference between the multi- and the single-social condition, although previous work suggested that social influence increases with group size (Bond, 2005). One reason could be that the manipulation of group size was not salient enough, inducing participants to underestimate the additional predictive power of large groups (Mannes, 2009).

For participants who relied on social information, the computational modeling suggested that the majority of participants was better described by a two-step integration model than a single-step integration model, with the two social choice models being 2.5 times more likely than the social cue model, assuming a single-step integration process. Within the social choice models, more than half of the participants were better described by the SC_{CPM}, which assumes that people do not consider the specific cue patterns. One reason why participants relied more on the simpler classification process could be that with the social information, the already difficult classification task increased in complexity leading some participants to give up, ignoring the cue patterns and just following the social information. The increased complexity in the social conditions might also explain why social information did not improve performance overall. We will discuss this issue in more detail in the general discussion.

In our task we presented the social information together with non-social information. In real life, however, social information is often not received at the same time point as non-social information, but either before or after people have had an opportunity to consider the evidence on their own. Thus to replicate our findings and to generalize them to this novel situation, we conducted a second study in which we presented social information either before or after the object that had to be classified. How the temporal order would affect reliance on social information, however, was far from clear. On the one hand, a primacy effect of the information presented first might bias the processing in its direction (Germar et al., 2013). On the other hand, the temporal distance between information and corresponding feedback could decrease how much people rely on the information that is presented first, because it makes it more difficult to learn its validity (e.g., Maddox & Ing, 2005). We also took the opportunity to ensure that the length of the test phase in the individual compared to the social condition did not affect performance. In the first study, the test phase of the individual condition consisted of 160 trials, which was considerably shorter than the test phase of the social conditions (240 trials). To get a more robust comparison and to ensure that each item was presented equally often, we use the same number of trials for all conditions in Study 2.

Study 2

The goal of Study 2 was to investigate whether a temporal disassociation of non-social and social information changes whether and how social information is integrated into the decision process. The social and non-social information were presented at different time points: In the social-first condition the social information was presented prior to the objects that had to be classified and in the social-second condition the social information was presented after the objects had been shown. Furthermore, Study 2 also addressed a possible confound of Study 1 by making the test phase more comparable between the conditions.

Methods

Participants

Sixty participants (38 female, 22 male) aged on average 23 years (range 20–39) took part in Study 2, with 20 participants per condition. Participants were recruited from the student participant pool of the University of Basel. The duration of the study was approximately 45 minutes. Participants were paid depending on performance and gained on average 25.3 Swiss francs in the individual condition, 25 Swiss francs in the social-second condition, and 24.9 Swiss francs in the social-first condition.

Classification Task

The study consisted of three between-subjects conditions. Participants solved the same classification task as in Study 1. In the individual condition no social information was presented. In the social-first condition, social information was provided before the non-social information about an object was presented. In the social-second condition, social information was provided after the object was presented. Participants could decide freely how long they wanted to observe each piece of information; information remained on the screen until they opted to see the next piece of information / made a decision. In both conditions the two pieces of information were never observed concurrently; when participants chose to see the next piece of information, the first was removed. Social information was provided in half of the trials, but the order was randomized within a block of training objects so that participants would not know if the next trial contained social information or not. Last, unlike in Study 1, the test phase in all three conditions consisted of 240 trials reflecting the test phases in the social conditions and we now used the same old items from the training phase as in the social conditions. Otherwise, Study 2 followed the same procedure and used the same materials as Study 1.

Results

Performance

Training. Like in Study 1, we compared classification performance between the three conditions and analyzed the change in performance over time. A repeated measures ANOVA, with block as within-participant factor and condition as between-participant factor and the percentage of correct classifications as dependent variable, showed no significant main effect of condition $F(2, 57) = .07$, $p = .94$, $\eta^2 = .002$, a significant main effect of block, $F(6.81, 388.33) = 33.28$, $p < .001$, $\eta^2 = .37$, and no significant interaction between block and condition, $F(13.6, 388.33) = .57$, $p = .89$, $\eta^2 = .02$. As illustrated in Figure 5 (panel A), this suggests that participants learnt to solve the task, but performance did not differ between the conditions.

Test. As in Study 1, we focused on the new test objects to investigate whether classification performance in the social conditions depended on the quality of observed information and to compare performance between the individual and social conditions.[2] Again, we conduct a repeated measures ANOVA, with quality of observed information (incorrect, none, correct) as within-participant factor, condition as between-participant factor, and the percentage of correct classifications as dependent variable. As illustrated in Figure 5

[2] To compare performance in the individual and social conditions we used for each object in the social condition (separate for type of social information) the respective repetition of the object in the individual condition. As in Study 1, the pattern of results stays the same if all objects and not only the new test objects are considered.

(panel B), the analysis showed a significant main effect of quality of information, $F(1.25, 71.53) = 26.41$, $p < .001$, $\eta^2 = .32$, and a significant main effect of condition, $F(2, 57) = 5.6$, $p = .01$, $\eta^2 = .16$, suggesting that performance improved with correct social information and that across all object types participants in the individual condition performed better than in the social conditions. A Tukey post-hoc test showed a significant difference between the individual condition and each of the social conditions (all $p < .02$). In addition, we found a significant interaction between quality of information and condition, $F(2.51, 71.53) = 13.14$, $p < .001$, $\eta^2 = .32$, suggesting that the effect of quality of information differed depending on the condition. Follow-up analysis on the influence of quality of social information separately for the three conditions showed that performance was strongly affected by the quality of information in the social-second condition (linear trend: $F(1, 19) = 24.6$, $p < .001$, $\eta^2 = .56$), and also slightly in the social-first condition (linear trend: $F(1, 19) = 5.1$, $p = .036$, $\eta^2 = .21$), but — as expected — not in the individual condition (linear trend: $F(1, 19) = 1.33$, $p = .26$, $\eta^2 = .065$).

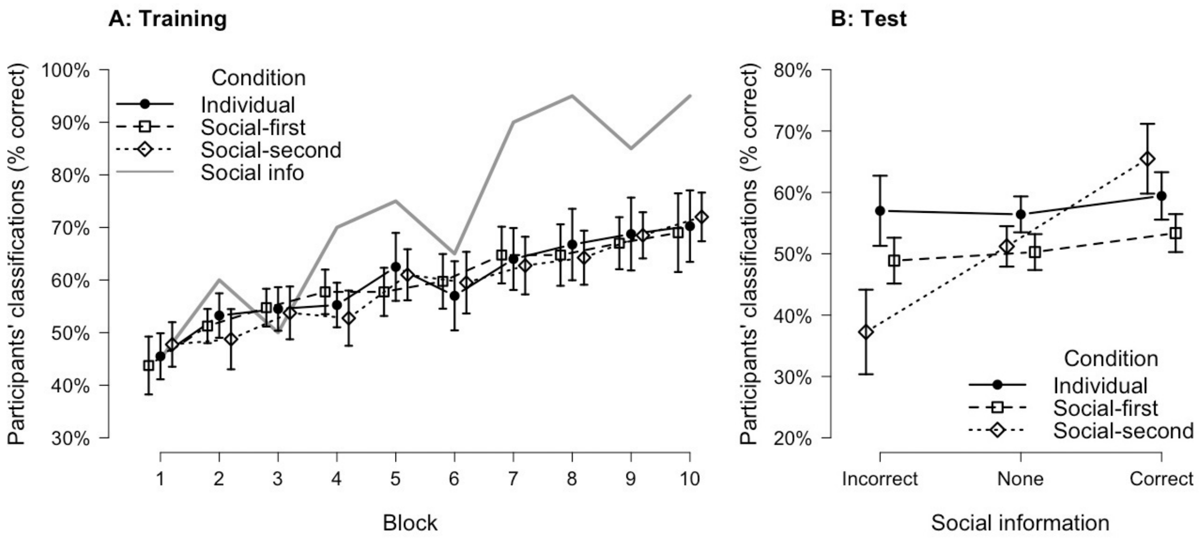

Figure 5. The left panel (A: Training) shows the learning performance in the training phase of Study 2. Each block consists of 20 trials. Error bars denote a 95% confidence interval. The right panel (B: Test) shows the interaction of information quality and condition in the test phase of Study 2 for the new test objects. In the individual condition, no social

information was presented. The labels “correct” and “incorrect” social information denote the respective repetitions of the objects that were presented with correct or incorrect social information in the social conditions. Error bars indicate 95% confidence intervals. Please note the different scaling of the y-axis across panels.

Quantitative model comparison

Model estimation and model evaluation were performed analogous to Study 1. Table 3 summarizes the modeling results.

In the individual condition, 14 participants were best described by the GCM and 6 participants by the CPM. Figure 6 gives an overview for the Bayesian model weights for each model separated for the two social conditions. In the social-first condition, 12 participants were best described by the GCM, 5 by the CPM, 2 by the CUE model and 1 by the SC_{CPM}. In the social-second condition, 7 participants were best described by the GCM, 2 by the CPM, 5 by the SC_{GCM}, 3 by SC_{CPM} and 3 by the CUE model. A comparison of evidence strength shows a 2.2 ratio in favor of social choice models over the CUE model.

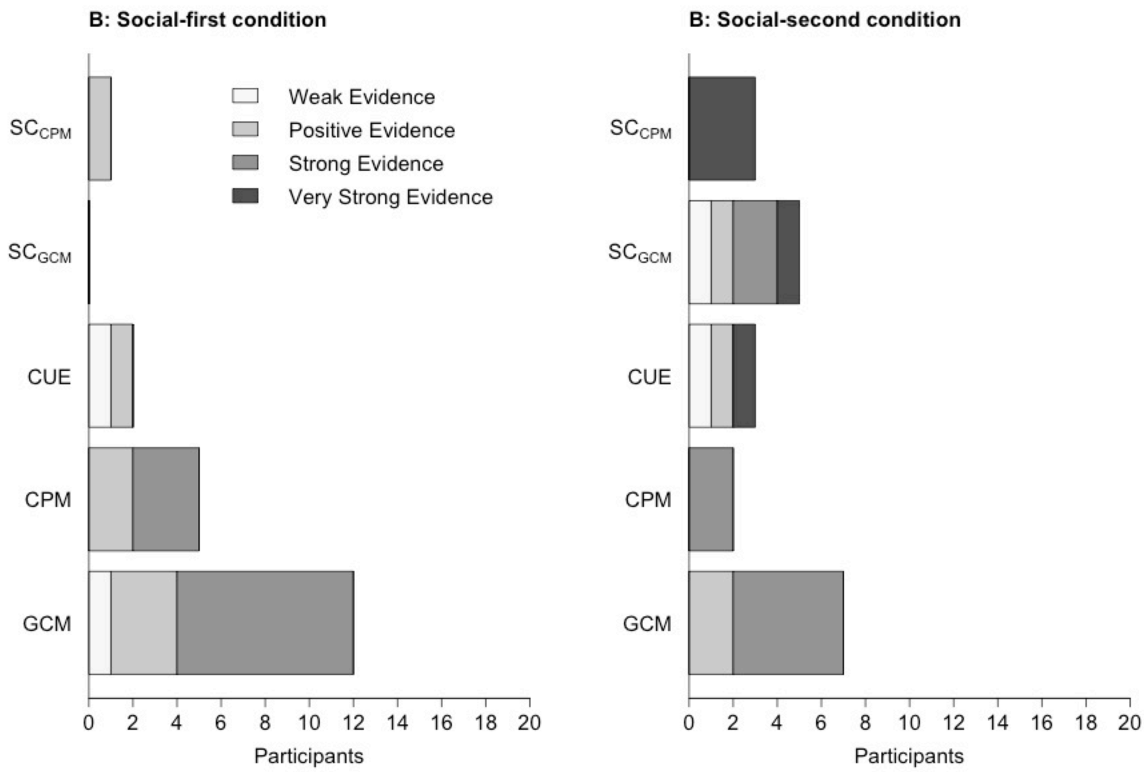

Figure 6. Evidence for each model per participant of Study 2. Bayesian model weights for the classified participants of the (A) social-first condition and (B) social-second condition. GCM = general context model; CPM = constant probability model; CUE = cue model; SC_{GCM} = social choice (general context model); SC_{CPM} = social choice (constant probability model).

In sum, modeling results of Study 2 show that when information was presented before the decision, it was largely ignored and classifications were mainly based on the non-social cue information, whereas when social information was presented after the objects had been presented, it was treated similarly to when it was presented simultaneously with the non-social cues as in Study 1. Furthermore, in comparison to Study 1, slightly more people were classified to the SC_{GCM} than the SC_{CPM} model.

Discussion of Study 2

The goal of Study 2 was to replicate the findings of Study 1 and investigate whether temporal order of information changed the influence of social information in classification decisions. The study consisted of three between-subjects conditions: In the individual condition participants solved the task individually, in the two social conditions participants additionally observed decisions of another person either before or after observing the object. Overall, we replicated the results from Study 1. In general social information influenced responses, with participants performing better with correct social information than with no or incorrect social information. Furthermore, when social information was used, the modeling analyses suggested that it was integrated in a two-step integration process.

In addition, our results indicated that the presentation order influenced how strongly social information was considered in the decision-making process. Presenting social before non-social information decreased social influence: The analysis of performance showed that the quality of social information strongly influenced performance in the social-second condition, but only slightly in the social-first condition. In addition, the modeling analyses suggested that only a minority of participants relied on social information when it was presented before the objects, whereas more than half of the participants making classifications were best described by a social model when social information was presented after the non-social information. These results suggest that temporal distance decreases the influence of social information, resonating with research showing that delayed feedback can decrease learning (Maddox & Ing, 2005).

General Discussion

The current work shows that social information affects decision making in a classification paradigm. In contrast to other paradigms that have found clear benefits of providing good social information (Biele et al., 2009, 2011; McElreath et al., 2005), social information did not increase overall performance in our tasks. Nevertheless, we found that classification decisions shifted in the direction of social information, suggesting that participants integrated it in their decision process. In addition, our results suggest that cognitively social and non-social information are integrated in a weighted, additive manner;

that is, people first form their own opinion based on non-social information, which is then compared to and integrated with social information in a second step.

Influence of Social Information on Performance in Classification Decisions

Research on social influence in categorization has shown that children strongly benefit from social information: Observing an adult helps children to discover relevant features and the rules underlying category membership (Butler & Markman, 2014; Elsner & Pauen, 2007; Taverna & Peralta, 2012; Wang, Meltzoff, et al., 2015; Wang, Williamson, et al., 2015), yet it was unclear whether adults likewise benefit from additional social information. Although we did not find an overall increase in classification performance, our results indicate that social information influenced performance conditional upon the quality of information: When participants observed correct information, it led to better classification performance in the conditions where participants clearly considered social information. In contrast, observing incorrect information led in all social conditions to worse performance compared to participants who learned individually. Furthermore, we found that in the test phase in Study 2, participants in the social conditions performed overall worse than participants in the individual condition. Although these findings are in line with research suggesting that social information might impair individual learning because it provides incentives to participants to pay less attention to the non-social information (Morgan, Rendell, Ehn, Hoppitt, & Laland, 2012; Rendell et al., 2011), it is important to note that we did not find any performance differences during training and in the test phase in Study 1, even though in our task adding social information also increased the complexity of the task. In half of the trials social learners had to deal with an additional piece of information compared to the individual learners, which could have made it more difficult to learn how to use the non-social cues for the classification decisions. Accordingly, our studies should not be taken as evidence that the presence of social information per se impairs learning from non-social information. However, further research to determine if and when social information can harm individual learning processes is desirable. Importantly, future studies should only change the labeling of the information while keeping the complexity and the validity of the social and non-social cues comparable, as well as consider the question whether the influence of social information changes depending on the complexity of the task.

However, our results show that providing social information in addition to non-social information — as may be frequently the case in many everyday life situations — will not always facilitate learning, even if the social information is valid. As mentioned above, one reason could be the increased complexity created by the additional information. However, other studies have found beneficial effects of social information in similar designs with children (Wang, Meltzoff, et al., 2015; Wang, Williamson, et al., 2015) and in other decision-making paradigms (Biele et al., 2009, 2011; McElreath et al., 2005). There are two further reasons why we did not find beneficial effects of social information. For one, in our studies participants only received social information in half of the trials, which could have weakened the reliance on social information. This would suggest that the spacing of social information is important and may be a moderator of its effect on learning. Second, we provided the choices of another person who also had to learn the task from scratch. Accordingly, this person did not perform very well in the beginning of the task. This could have led participants to believe that the social information in general was of low validity and thus they decided to ignore it for the remainder of the task. It is therefore possible that the beneficial effect of social information would be stronger if it provided valid advice from the beginning of the learning phase.

In this vein, another interesting avenue for future research might be the question of how changes in the validity of social information influence how much it is used. The way social information is implemented in the literature depends largely on the research question at hand; studies on advice usually give social information only once, in a “one-shot” manner, before the task has to be solved (e.g., Biele et al., 2009; Meshi et al., 2012; Yaniv, 2004). In contrast, studies on social learning provide social information repeatedly during the task; relatively few studies exist that provided social information with a validity that does not change during the task (Collins et al., 2011; Germar et al., 2013). Most studies have used the real behavior of other persons, which either has been pre-recorded (e.g., Morgan et al., 2012; Toelch, Bach, & Dolan, 2013) or is presented in real time during the task (Derex et al., 2012; McElreath et al., 2005). The two later implementations imply some variability in the validity of the observed behavior. These studies have found mixed results: Derex et al. (2012) found that showing the outcome of real decisions did not help the observer, but observing the process did. In contrast, McElreath et al. (2005) found that also social information of varying validity can improve performance. However, past work differs in many aspects other than the stability of the validity of the social information, thus indicating the need for further research.

Factors Moderating the Influence of Social Information

In addition, our studies give some indication about when social information is more likely to be considered. Study 1 suggested that it does not make a reliable difference whether social information is believed to come from a single individual or a group of people, although the effect of social information was somewhat more pronounced in the multi-social condition. Furthermore, Study 2 suggested that the presentation order influenced how strongly social information influenced the classification decisions. When social information was presented before the non-social information, it influenced behavior less than when it was presented after the non-social information. This decline in social influence is in line with research on the decrease of the influence on feedback with longer time delays (see Maddox & Ing, 2005). However, it is possible that these results depend on the importance assigned to the social information (Toelch et al., 2009).

Integration of social and non-social information in classification decisions

Using a computational modeling approach we investigated how people integrate social and non-social information when solving a classification problem. Overall, our results suggest that social and non-social information are integrated in a computationally segregated fashion following a two-step process (Behrens et al., 2008; Collins et al., 2011). In Study 1 and the social-second condition of Study 2, models assuming a two-step integration process best described the majority of participants who used social information; that is, they assume that when making classification decisions people first form an individual opinion regarding the category to which the object belongs, based on the object's attributes, and then adjust this opinion based on the observed social information and its validity. These findings resonate with research in decision making suggesting that different brain areas are involved when processing social and non-social information (e.g., Behrens et al., 2008; Burke et al., 2010) and the general idea that people weight social information against their own opinion (Huber et al., 2015; Yaniv, 2004).

Nevertheless, a minority of participants was best described by the CUE model, which assumes that social information is used just like any further cue, suggesting that some people do not treat social information as qualitatively different. Here, further research is necessary to specify when social information is treated as qualitatively different and when it is considered in the same way as non-social information.

Conclusion

In sum, although social information in the two studies presented did not influence overall performance, we found that it reliably influenced classification decisions, by leading individuals towards specific decisions. Furthermore, our results suggest that the cognitive apparatus separately evaluates social and non-social information, and then integrates them in a second step. The current work establishes a basis on which further research can build to jointly investigate two pervasive phenomena in human daily functioning: The imperative to classify things in our environment and the social situations in which such decisions take place.

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Tables

Table 1

Overview of the stimulus material used in Study 1

Object	Cue 1	Cue 2	Cue 3	Cue 4	Cue 5	Criterion	Phase
1	0	0	0	0	1	1	training
2	0	0	0	1	0	1	both
3	0	0	0	1	1	0	training
4	0	0	1	0	0	1	both s
5	0	0	1	0	1	1	both i
6	0	0	1	1	0	0	both
7	0	0	1	1	1	0	test
8	0	1	0	0	0	1	test
9	0	1	0	0	1	0	both s
10	0	1	0	1	0	1	both s
11	0	1	0	1	1	0	training
12	0	1	1	0	0	1	training
13	0	1	1	0	1	1	both i
14	0	1	1	1	0	1	test
15	0	1	1	1	1	1	test
16	1	0	0	0	0	1	both
17	1	0	0	0	1	0	test
18	1	0	0	1	0	0	both i
19	1	0	0	1	1	1	test
20	1	0	1	0	0	1	both
21	1	0	1	0	1	0	training
22	1	0	1	1	0	0	test
23	1	0	1	1	1	0	both
24	1	1	0	0	0	1	test
25	1	1	0	0	1	0	training
26	1	1	0	1	0	1	both
27	1	1	0	1	1	1	both
28	1	1	1	0	0	0	test
29	1	1	1	0	1	1	training
30	1	1	1	1	0	1	test

Note: 0 = red, 1 = blue. The column *Object* denotes a number that identifies the object. Objects are sorted according to the cue values. The column *Criterion* denotes the category to which the object belonged. The column *Phase* denotes the phase in which the object was shown to the participants (training = only during training, test = only during test, both = during training and test). In the test phase of the individual condition, we included the objects 4, 9 and 10 that had appeared in the training phase (both i). In the social conditions, we instead used the objects 5, 13, and 18 (both s) to increase discriminability of the models.

Table 2

Summary of the quantitative model comparison of Study 1: means (*M*) and standard deviations (*SD*)

		Individual condition		Social conditions				
		GCM	CPM	GCM	CPM	CUE	SC_{GCM}	SC_{CPM}
-2 LL	*M*	235	295	349	411	334	334	388
	SD	62.1	16.8	62.4	6.8	61.7	62.4	27.8
BIC	*M*	262	300	378	417	368	368	399
	SD	62.1	16.8	62.4	6.8	61.7	62.4	27.8
BIC weight	*M*	.7	.3	.36	.07	.16	.18	.23
	SD	.47	.47	.39	.22	.26	.28	.39
Social para-meter	*M*	-	-	-	-	.42	.27	.08
	SD	-	-	-	-	.56	.21	.1

Note. Quantitative model comparison for Study 1. GCM = general context model; CPM = constant probability model; CUE = cue model; SC_{GCM} = social choice (general context model); SC_{CPM} = social choice (constant probability model). Denoted are the means and standard deviations for -2 log likelihood, BIC and Bayesian weights of each model in each condition. Goodness-of-fit indices between the individual and social condition are based on different number of trials and thus cannot be compared directly. The social parameter denotes the free parameter reflecting the weight given to the social information.

Table 3

Overview of the model evaluation in Study 2

		Individual condition		Social-first condition					Social-second condition				
		GCM	CPM	GCM	CPM	CUE	SC_{GCM}	SC_{CPM}	GCM	CPM	CUE	SC_{GCM}	SC_{CPM}
-2 LL	*M*	344	391	348	492	332	331	384	350	400	348	349	400
	SD	51.4	78.9	53.6	24.9	47.7	47.0	28	50.0	24.7	49.2	49.1	26.7
BIC	*M*	373	396	377	498	366	365	395	378	412	383	383	412
	SD	51.4	78.9	53.6	24.9	47.7	47.0	28	50.0	24.7	49.2	49.1	26.7
BIC weight	*M*	.69	.31	.35	.10	.17	.22	.16	.53	.24	.10	.05	.09
	SD	.46	.46	.39	.29	.27	.33	.36	. 40	.39	.14	.04	.2
Social parameter	*M*	-	-	-	-	.11	.23	.35	-	-	.07	.05	.14
	SD	-	-	-	-	.18	.24	.22	-	-	.07	.07	0.10

Note. Quantitative model comparison for Study 2. GCM = general context model; CPM = constant probability model; CUE = cue model; SC_{GCM} = social choice (general context model); SC_{CPM} = social choice (constant probability model). Displayed are the means and standard deviations for -2 log likelihood, BIC and Bayesian weights of each model in each condition. The social parameter denotes the free parameter reflecting the weight given to the social information.

Figure Captions

Figure 1. The figure illustrates how the different objects were presented to the participants in Study 1. The left panel (A) shows an example trial of the individual condition or a non-social trial in one of the social conditions. The middle panel (B) shows a social trial of the single-social condition, while the right panel (C) shows a social trial of the multi-social condition. Stick figures indicated the social information (i.e., the decision of the presented participant/s) in a given trial.

Figure 2. The left panel (A: Training) shows the learning performance in the training phase of Study 1. Each block consists of 20 trials. Superimposed is the performance of the participant whose data was used as social information. Error bars denote a 95% confidence interval. The right panel (B: Test) shows the performance as a function of the information quality and the social condition in the test phase of Study 1. Please note that in the individual condition no social information was presented. The labels "incorrect", "none" and "correct" social information denote the respective objects that were presented with incorrect, no or correct social information in the social conditions (see also Footnote 1). Error bars indicate 95% confidence interval. Please note the different scaling of the y-axis across panels.

Figure 3. Evidence for each model per participant of Study 1. The left panel (A: Individual condition) shows evidence for the individual condition and the right panel (B: Social conditions) for the two social conditions put together. GCM = general context model; CPM = constant probability model; CUE = cue model; SC_{GCM} = social choice (general context model); SC_{CPM} = social choice (constant probability model).

Figure 4. The figure shows scatter plots of participants' classification probabilities and model predictions in the individual and social conditions. Panel A shows participants' and the GCM's classification probabilities for the individual condition. Panels B to D show participants' and model's classification probabilities for subjects of both social conditions jointly, with panel B showing the GCM, panel C the CUE model, and panel D the SC model. Each panel shows the data of the participants who were described best by the respective model.

Figure 5. The left panel (A: Training) shows the learning performance in the training phase of Study 2. Each block consists of 20 trials. Error bars denote a 95% confidence interval. The right panel (B: Test) shows the interaction of information quality and condition in the test phase of Study 2 for the new test objects. In the individual condition, no social information was presented. The labels "correct" and "incorrect" social information denote the respective repetitions of the objects that were presented with correct or incorrect social information in the social conditions. Error bars indicate 95% confidence intervals. Please note the different scaling of the y-axis across panels.

Figure 6. Evidence for each model per participant of Study 2. Bayesian model weights for the classified participants of the (A) social-first condition and (B) social-second condition. GCM = general context model; CPM = constant probability model; CUE = cue model; SC_{GCM} = social choice (general context model); SC_{CPM} = social choice (constant probability model).